CHAPTER 2 - METHODS

2.1 - DEVELOPING A LIST OF EXPOSURE-RELEVANT TASKS

To develop a broad-based and yet concise list of exposure-relevant tasks, we reviewed a number of governmental sources of job classifications and job descriptions. Available data generally focused on the amount of time devoted to working, rather than the time spent in particular tasks while at work. Although there were numerous sources for job description information, much of the information we found was limited in that it only provided task information specific to one industry or job classification. The potentially useful source "Haz-Map"(http://www.haz-map.com /), an on-line "database of hazardous chemicals and occupational disease" that can be queried for task information related to specific jobs, was designed to be accessed by healthcare workers and industrial hygienists, but it did not contain much information relevant to MF exposures. Nonetheless, each source we examined was helpful in that it gave us an idea of methods to elicit occupational information and provided us with lists of common activities for various types of workers.

Since no source provided an exhaustive list of tasks, we determined that the best approach was to identify common jobs in the working population. One source provided comprehensive information on many types of jobs, namely, the State of California Employment Development Department. This information is specific to California workers and can be found on the Development Department's Labor Market Information web page http://www.calmis.cahwnet.gov/. We used the table "Occupational Employment Projections 1993-2005 California, " which provided information about the annual average number of workers in each occupational employment statistic (OES) category in 1993. We were thus able to determine the most prevalent jobs in California. The OES coding system is similar to other classification systems such as the Standard Occupational Classification (SOC) coding system and the U.S. Bureau of Census (BOC) coding system. A "cross-walk" listing that linked the OES codes to other coding systems such as the SOC and BOC was provided in association with this table.

OES categories were ranked from highest to lowest prevalence, according to the number of workers. We extracted the OES categories that comprised the top 80% of jobs in

California. We also incorporated both the top and bottom 15% of jobs in the University of Washington job-exposure matrix (JEM) (Touchstone et al. 1999) to ensure that jobs with a range of magnetic field exposures were included in our list. Independent of this project, Prof. M. Yost and J. Touchstone have developed a JEM for EMF for use in the brain cancer study conducted by Dr. Wrensch in California. The JEM contains EMF exposure data for over 200 common occupations representative of the general population. Also, from Dr. Wrensch's study (and from Census data), we obtained information on the relative frequency of these jobs in the general population. Jobs in the UW JEM were in SOC format and had to be translated to OES format using the "cross-walk" listing mentioned above. With the addition of these jobs, 86 % of the working population of California is covered by our list. There are a total of 206 jobs included on our common job list. Jobs are listed in the order of their frequency within the population of California (see Appendix).

We were able to locate electronic files of detailed job descriptions from "The California Occupational Guides, Emerging Guides, and Emerging Occupations" also from the California Employment Development Department web page: http://www.calmis.cahwnet.gov/. The guides are a series of information sheets covering individual occupations or groups of occupations. They contained detailed job descriptions for 70% of our most common jobs (see the "description" column in the Appendix – a "y" indicates a detailed job description was available). Below is an example of an excerpt from this guide pertaining to butchers:

BUTCHER
California Occupational Guide #218
Interest Area 5-E
Meat Cutters work in conventional markets or in self-service departments of supermarkets. Meat Cutters divide the primal cuts into chops, steaks and other retail cuts and also prepare poultry and fish for retail sale. Meat Cutters also may **weigh, wrap, and label** the cuts and arrange them in **refrigerated cases** for display to customers. They also may prepare special cuts of meat ordered by customers.

In wholesale meat firms, Butcher apprentices begin their training by performing odd jobs in the plant. For example, they may learn meat pickling. Training includes instruction in the **operation of such equipment as forklifts or power-driven saws and grinders**. In time, apprentices gradually learn to divide whole carcasses, halves, and quarters into primal cuts. In retail establishments, Meat Cutter apprentices begin by preparing some of the cheaper cuts. They learn to bone meat and roll and tie roasts. They also learn how to set up a counter display, merchandising and salesmanship, and how to answer customer questions concerning meat preparation and cooking.

Figure 2-1. Example Job Description from The California Occupational Guides

The words in bold indicate tasks performed by butchers that could have related MF exposure. These definitions were useful because they often provided information on tasks that might not have been self-evident, such as a butcher's use of forklifts. The same web site also had limited job descriptions (two to three sentences long) for the remaining jobs for which we did not have detailed descriptions.

All job descriptions were examined in determining common tasks. We focused on tasks that can drive MF exposure higher than baseline. A list of common tasks was then developed based on these standardized job descriptions, with particular attention paid to tasks having potential for MF exposure. The task list underwent review within our research group. We considered the following questions:

1. Is this list adequate, and does it cover a broad enough range of tasks?
2. Have we missed any tasks that may be inherent in the group of common jobs that we didn't consider for our task list?
3. How does the environment someone is working in affect MF exposure?

We continued to refine the list of common exposure-relevant tasks by incorporating ideas generated from our previous literature review. Descriptions of each task were designed to be clearly understandable and mutually exclusive to the extent possible. Simultaneously, we created a list of MF sources that are potentially encountered for each task (see Discussion). A significant secondary review of the job description information was conducted to refine the database containing the common tasks and related job titles to make sure that no tasks were omitted and to update the database to reflect the modifications in the common task list. Thus, each full text job description and partial job description was thoroughly reviewed twice.

We examined the distribution of workers in each job code category for OES codes that did not have any "official" text descriptions (13% of jobs on the most common job list):

Table 2-1. Job Categories not Found in The California Occupational Guides

General mangers, top executives	Misc helpers, laborers, hand, nec[A]
Typists, including word processing	Combined food prep and service
Stock clerks--sales floor	Financial mangers
Computer programmers, incl aides	Mkting, adv, pub-rel managers
Gardeners, groundskeepers-ex farm[B]	Management support workers, nec[A]
Misc ag, forestry, fishing[B]	Sales and related workers, nec
Counter attendants--food	

[A] limited job description data in same OES category
[B] no job description data in same OES category

For most of the above categories, we have full text descriptions for similar jobs in the same OES category, so that tasks likely found in these categories were already on our task list (exceptions are noted in the table above). We did this exercise to assure that we were not "missing" any tasks that may form a part of these jobs. Based on this survey we are confident that tasks common in these occupations are also found on our common task list.

2.2 - QUESTIONNAIRE DEVELOPMENT

From the list of exposure-relevant tasks, we developed a task-based time-log questionnaire instrument. We planned to combine this information with existing task-exposure data, to be able to estimate a worker's average exposure for a typical day. The questionnaire could then be evaluated by collecting personal exposure measurements for workers who completed the questionnaire, and this process could then help us to determine which tasks most influence MF exposures.

While questionnaires have normally been administered using a printed instrument, increasingly, researchers are turning to computerized formats. A printed format works well when it is necessary to collect time-log information from workers because it is convenient for them to carry around a piece of paper and record tasks as they do them. An electronic format is suitable when the task information desired does not need to be specific moment-by-moment, but rather can be collected at any time. An interactive web-based questionnaire extends the computer-based format to make the questionnaire available to anyone with Internet access. For this study, we created a prototype electronic questionnaire, described below.

2.2.2 - Identifying Available Data

In order to be able to estimate task exposures, we needed to identify task-specific exposure information. Various sources for MF personal exposure data were explored, but little data exists on measured, task-specific exposure. Data from the Department of Energy (DOE) 1000-Person Study best fit our purposes (Zaffanella and Kalton 1998). This study logged 24-hour exposure data using the *EMDEX-PAL* exposure meter (Enertech Consultants, Inc.). The resulting database contains magnetic field statistical summaries for each 10-minute period throughout an entire 24-hour measurement period. Each person has an occupational description, which corresponds to an occupational classification code. There is a diary of each person's activities during the 24-hour measurement period. Although this study collected personal exposure, work descriptions, and location diary information, it was not possible to extract data correlated to specific tasks. For example, a person may be identified as a "computer programmer" who worked for 8 hours during the 24-hour period, and there is a TWA for the magnetic field during this work period. However, we do not know if the person was working at his computer the entire time, if he attended meetings, or went to a seminar, etc. and we do not know what sources were encountered during the work period.

The tasks on the task list we developed were compared to a list of occupational descriptions and codes from the National Occupational Classification to determine which occupations were related to each task (see Appendix). An occupation was considered related to a task if that task is typically performed in that occupation. For example, a welder would be related to the task of *welding*. Occupations such as mathematical scientists, computer programmers, and secretaries were thought to be related to the task, *computer data entry or retrieval* because people in these jobs are often at a desk using a computer. Some task/occupation combinations matched closely, while others had a weaker relationship. No occupations were found to be related to the tasks *operating a ship, airplane, train, or trolley; operating/tending an electric furnace or heating device*, and *lunch/break*. An overall mean for each task was calculated by combining data from all the related occupations that had data available in the 1000-Person Study. It should be noted that data was not available for all the task/occupation relationships listed in the Appendix. In some instances, occupations were matched with more than one task category. Carpenters were associated with operation of both *use of electrical tools* and *use of non-electrical tools*. This means that data from the same occupation was used to estimate two different tasks which causes there to be less differentiation between task estimates.

2.2.3 Web-based Questionnaire

A prototype electronic questionnaire, designed around the task list, was developed in basic HTML code (see Appendix). The electronic questionnaire asks workers if they do each of the common tasks on a typical day, with response choices "yes," "no," and "need more information." If "need more information" is chosen, the hyperlink points to a definition that further describes the task. If "yes" is chosen, there is an input box to enter the hours per day (frequency) the worker does the task. When a worker selects a specific task, a table is called upon that has an exposure value associated with each task. The main part of the questionnaire involved the common tasks we identified. We explored the possibility of adding another separate part of the questionnaire that involved specific sources encountered at work, such the intensity with which a task was performed or sources, environments, and conditions related to the task. Exposure data was available from Enertech for appliances, machines, and other sources. However, we decided not to include sources in our prototype questionnaire, since the issue of how tasks and sources relate to each other is complicated, and we did not want to determine *a priori* which sources belong to which tasks.

Currently, the web-based questionnaire takes self-reported task and time data and estimates an average daily exposure. A web-based tool for data entry and presentation of an individual's EMF average and percentile ranking could have the following additional functionality:

- Web form for data entry of selected demographic data and time worked in defined task categories.
- Additional web pages with supporting/explanatory information
- Table with category-specific, time weighted average EMF factors
- Table with percentile distribution for working adults
- Calculate and display the weighted average and percentile rating.
- Send email to designated person with data and results

We received feedback on the task list and draft web questionnaire following our presentation to the Stakeholders Advisory Committee in February 2000. We made every effort to incorporate these ideas in our project. A summary of the communications at this meeting can be found in the Appendix.

2.3 - QUESTIONNAIRE FIELD-TESTING AND EVALUATION

We were not able to locate a feasible California population in which to test the questionnaire, so we selected a population from an ongoing study of melatonin production in EMF-exposed utility workers at Colorado State University in Fort Collins, CO. We subcontracted with investigators at CSU, Dr. John Reif and Dr. Jim Burch, to pilot test the questionnaire on their study population. The population was comprised of workers at several electric utilities in the Ft. Collins area. While the majority of the population consisted of utility workers, there was a significant portion of office workers (~40%) included in the population. As part of the CSU study, these workers wore an EMDEX meter over a period of four days, on four separate occasions, during a one-year period, for a total of up to 16 days of monitoring per worker. During each sampling period (typically three days), they completed an activity log for each day of work to record activities that they participated in while at work. They also completed a time log to indicate times they arrived and left both home and work.

A task-based time-log, specific to our task list, but tailored to the CSU population (see Appendix) was developed to replace the time-activity log that they had been using. This study's version of the task log will be referred to as the University of Washington (UW) task log. We chose to use an activity log format (printed version) of our questionnaire for this evaluation since this format was already being used with study subjects. This format elicited the same information as the electronic version would. It allows workers to tell us whether or not each task was performed and provides us with information on duration and frequency of each task.

Our task log was used during one workday (usually the second) during the fourth sampling phase. The log we created served a dual purpose; it needed to capture the same task information as the CSU log since the CSU study was still in progress, and it needed to capture information about the tasks we were interested in. Although the tasks listed on the CSU task log had been developed independently of our task list, there were several common categories (CSU categories tended to be more general). Consequently, it was straightforward to modify the CSU task log, and the workers were already familiar with the format.

Due to space constraints on the one-sheet (front and back) task logs, some of the common activities on our list were omitted from the CSU task log. The activities omitted included: *ship, airplane, train, trolley*; *biomedical/analytical equipment*; *electric furnace or heating devices*; *x-ray equipment*; *cooking/food preparation*; *personal services*; *production assembly work*; and *retail checkout*. There also was an "*other*" category for them to write in an activity not found on the log. The title of the category, *operating/tending industrial machinery*, was slightly revised to make it more understandable to study subjects.

The basis for deciding which categories to eliminate was decided by CSU study investigators who were familiar with activities reported by subjects in previous activity log surveys. It is highly unlikely that these activities that would be performed by the CSU population. We split our *electrical utility work and wiring* category into environment categories of *three phase*, *single phase*, *non-energized phase*, and *substation,* which already existed on the previous CSU activity log, and had been found to give meaningful exposure information. Since some workers were actually doing electrical work as a main component of their jobs, more specific categories were necessary to describe in better detail how they spent their time. As mentioned above, it was necessary to keep the activity log consistent with the CSU version. Work on the specialized questionnaire for the CSU population helped further refine our list of tasks.

Our task log had a list of the task categories across the top of the page and blocks of time down the left side of the page in one-hour blocks. A worker indicated when a task was performed by drawing a line or arrow or filling in the boxes from the start time to the end time for that task. Instructions were provided on how to record fractions of an hour, using a horizontal or diagonal line to "split a box" into finer increments. For the time log, workers recorded time in hours and minutes. Useful information on the time log included time of departure from home, arrival at work, departure from work, and arrival back at home.

2.4 – EVALUATING THE TASK-BASED APPROACH

As a preliminary means of evaluating the task-based time-log approach, we compared exposure estimates developed from the questionnaire with personal exposure data captured by the EMDEX on the day the task was performed. Unfortunately, when we began the evaluation study, CSU already had started the fourth phase of sampling, and only about half of the subjects (43 out of about 70 possible) remained to be sampled. These subjects completed our task log on the second day of their monitoring and we used the corresponding personal measurements from this second day for the validation.

Another aspect of our evaluation involved collecting "spot" (short-duration, location-specific) measurements. Research staff at CSU examined the tasks reported by subjects on task logs (at the end of their 4-day sampling period) to determine suitable work locations to measure. For instance, if a worker monitored a control panel for part of his day, it would be feasible to take spot measurements at the control panel station. However, if a worker spent the day working on power lines, it would be difficult to get meaningful spot measurements 1) because of the physical location of the lines, and 2) because the lineman's work environment is constantly changing. Since the spot measurements were usually taken on the fourth day of the sampling period, there was a delay of a few days between the time the personal and spot measurements were taken. Where feasible, spot measurements were taken at each location where a worker performed a task (see Appendix). Spot measurements were collected while the task was taking place (with the sources turned on), and were also collected to capture the background exposure (with the sources turned off), in order to differentiate source-specific and general environmental contributions to exposure.

Task logs were reviewed from the first 3 1/2 (of 4) four-day sampling periods to determine if there were activities performed by these subjects that could help supplement our personal and spot measurement data set. We used some personal data from subjects who had already been measured during the first half of the fourth four-day phase for task categories for which we were lacking data. In these cases, the worker did not complete a UW task log. We had a CSU task log for each workday, so we combined the personal data from all three workdays. By contrast, we only used the personal data from day 2 for workers who had completed our task log on day 2.

It was not possible to go back and gather spot measurements for subjects from the first three rounds, since the activities would have been performed 3 to 9 months previously and the work environment could have changed significantly. We returned to collect spot measurement data for some of the subjects from the first half of the fourth phase who performed activities for which we were lacking data. While this provided us with additional data, it was not as valuable. The work area environment may have changed even over just a few days time and the activity information was in the CSU task log format, not our format.

2.3.3 - Data from Field Test

CSU provided us with EMDEX files from each subject's 4-day sampling period. In our analysis we only used data from the fourth sampling period. This allowed us to extract personal exposure data for specific activities we were interested in. Also provided were the EMDEX files containing the spot measurements, a data collection form containing details of the spot measurement survey, and a completed task log for each subject and time log.

2.5 - DATA ANALYSIS

2.5.1 - Data Extraction

For each subject, we generated summary data using EMCALC (Enertech Consultants, Inc.) based on all occurrences of a task during a work shift (see Appendix). Resulting summary statistics were arithmetic mean (AM), standard deviation (SD), geometric mean (GM), geometric standard deviation (GSD), and number of observations (OBS) for each task that a worker performed either over one work shift or all three. If we had a UW task log for a subject, personal data was only extracted for the same work shift that the UW task log was completed (the second day). When we only had a CSU task log, data from all three work shifts was extracted.

A time log of hours worked was available for all subjects for all measured shifts regardless of whether there was a UW task log. Workers recorded time in hours and minutes. This information was used to clarify time periods when job activities and tasks were performed since it was often unclear from viewing the task log when the workers' shift ended.

When we only had CSU task log information available for a worker, we have to put this information in terms of our task categories. The *office work* and *travel/lunch break* categories on the CSU task log did not translate directly to the activity categories on our task log. Any marks in the *office work* category were equated with the *computer data entry or retrieval* on our activity log. We assumed that most people doing office work these days are either using a computer or have one at their desk. We felt it was less likely that someone performing office work would be using office/business machines the entire time. Therefore, the *computer data entry or retrieval* category fit best. The CSU *travel/lunch break* category was the same as our *lunch/break* category, although we didn't specifically tell workers to include travel time. It was evident that workers filling out the categories understood that these categories were equivalent. Most correctly chose the *gas/diesel motor vehicle* category if they traveled by car, versus choosing the *travel/lunch break* category.

2.5.2 - Re-creation of Exposure-Day

In addition to determining the feasibility of having workers record their daily tasks in log format while at work, we also wanted to determine if the resulting task-exposure model was internally consistent and plausible. As an initial check, we compared what the model would have predicted as each individual's average daily exposure based on reported tasks with each individual's measured exposure, using several different weighting methods. While the data used to generate the model was also used in this initial evaluation step, and was therefore not an independent sample, this step nonetheless allowed at least a preliminary evaluation of whether the task log was capturing reasonable data and whether the model was reflective of the important exposure determinants.

2.5.3 - Smith Weighting Method

We employed a method which weights individual observations by the proportion of the workday (measurement times) to estimate task means and variances (Smith et al. 1997). The method is meant to be applied to exposure data from task-based survey designs in which multiple workers are measured. The way data for this project was summarized is suggested by Smith et al. to have the least temporal autocorrelation between measurements. If the data used is, by contrast, based on just one fixed time period during one occurrence of a task, Smith et al. suggests the variance estimates may be biased due to autocorrelation. Ideally, the workers and measurement days would be randomly selected when using this method, but that was not possible with the population we used.

The following equation is used to calculate the task mean where each worker is weighted by his total measurement time:

$$\bar{x}_i = \frac{\sum_{j=1}^{n_i} W_{ij} \bar{x}_{ij}}{\sum_{j=1}^{n_i} W_{ij}}, \qquad 2.1$$

where $\bar{x}_i =$ individual subject's mean for the task derived from EMCALC

t_{ijk} = the measurement time for worker j on day k in task i

$W_{ij} = \sum_{k=1}^{n_{ij}} t_{ijk}$ which is the total time (in hours) spent by worker j in task i

The effective sample size (nhat) for task i is calculated by the following equation:

$$\hat{n}_i = \frac{\left(\sum_{j=1}^{n_i} W_{ij} \right)^2}{\sum_{j=1}^{n_i} W_{ij}^2} \qquad 2.2$$

This is used to calculate an estimated variance for the task.

$$V(\bar{x}_i) = \frac{\sum_{j=1}^{n_i} w_{ij} \left(\bar{x}_{ij} - \bar{x}_i \right)^2}{\hat{n}_i (\hat{n}_i - 1)}, \qquad 2.3$$

where w_{ij} is the W_{ij} rescaled:

$$w_{ij} = \hat{n}_i \frac{W_{ij}}{\sum_{j=1}^{n_i} W_{ij}} \qquad 2.4$$

The confidence interval of the mean was calculated as

$$\bar{x}_i \pm t_{(1-c)/2,df} \sqrt{V(\bar{x}_i)}, \qquad 2.5$$

where c=.95, and the degrees of freedom is $\hat{n}-1$

For the tasks *office/business machine*, *non-electric power tools*, *installing telecommunications networks*, and *welding*, nhat was set to 1.5 for the variance formula and degrees of freedom was set to 1.0 for the confidence interval formula. The same was true for the task of *freight handling/warehouse* work but only when using geometric statistics. The formulas would not have worked otherwise because only 1 or 2 measurements were available for those tasks: therefore, the confidence limits estimated for the categories may be too small.

We used another method described by Smith et al. in the same publication that uses the estimated task mean and variance computed over all subjects to recreate an individual subject's exposure day (see Appendix). This method is based on the proportion of time the worker spends performing each task.

The estimated mean for subject j, based on the proportion of time spent in each category and the estimated task mean and variance is calculated as follows:

$$\bar{x}_j = \sum_{i=1}^{n} p_{ij} \bar{x}_i , \qquad 2.6$$

where p_i is the fraction of time a worker spent in each task category (task i) as calculated below:

$$p_{ij} = \frac{W_{ij}}{\sum_{i=1}^{n} W_{ij}} \qquad 2.7$$

Estimated variance of the task mean is calculated by the following equation:

$$V\left(\bar{x}_j\right)=\sum_{i=1}^{n} p_{ij}^2 V(\bar{x}_i)\,, \qquad 2.8$$

where n is the number of tasks

The degrees of freedom used to recreate the subject's day is more involved than the formula used for task estimations. We employed the Satterthwaite approximation of the degrees of freedom for a linear combination of variances (Satterthwaite 1946).

$$df_j = \frac{\left(\sum_{i-1}^{n} p_{ij}^2 V\left(\bar{x}_i\right)\right)^2}{\sum_{i=1}^{n}\left[p_{ij}^2 V\left(\bar{x}_i\right)\right]^2 \Big/ \left(n_i - 1\right)} \qquad 2.9$$

The confidence interval of the mean was calculated as

$$\bar{x}_j \pm t_{(1-c)/2,df_s}\sqrt{V\left(\bar{x}_i\right)} \qquad 2.10$$

where c=.95

Geometric statistics were calculated using the same formulas. The natural logarithm of the geometric mean was substituted in the formulas in place of the mean and the results were exponentiated at the end to get the appropriate statistics. Geometric statistics are likely appropriate because the data was approximately log-normally distributed.

For comparison, we estimated overall task means and variances using three additional methods (no weighting, hourly weighting, and robust regression). The Smith method formulas were then used to recreate the subject's exposure using these three other task mean and variance exposure estimates.

2.5.4 - No-Weighting Method

The no-weighting method combines task data from individual subjects by a simple average. The amount of time spent performing each task was not accounted for in these calculations, therefore a task that was done for five hours was treated the same as a task performed for only one hour (see Appendix).

2.4.5 Hourly Weighting Method

The weighting by hours method simply weights each individual subject task mean by the number of hours spent performing the task. Each hour is treated as a unit of measurement. Hours spent in each task are derived by multiplying the number of observations associated with a task by the sampling rate of the EMDEX meter (See Appendix). This weighting scale of measurement for tasks was deemed reasonable, since observations in other studies have noted that short-term readings of MF exposure over an hour or more are relatively uncorrelated (van der Woord et al. 1999).

2.4.6 Robust Regression Method

Another approach to obtain task-specific exposure estimates is to use statistical modeling of the tasks, treating them as exposure determinants (Burstyn and Teschke 1999). Conceptually, this method can be described in the context of a multiple linear regression problem. In this analysis, the observed MF exposure ($\bar{x}_j$) for the j_{th} person's workday is the dependent variable, and the proportion of time p_i spent in each task i is a vector of predictor variables. Therefore, when the number of tasks is smaller than the number of subjects, least-squares regression methods can be applied to directly solve equation 2.6 and obtain "optimal" task-specific exposure estimates (in terms of explained variance) from the regression coefficients. The advantage of this technique is that it avoids the process of extracting data from each subject's workday measurements.

While straightforward in concept, several problems often arise with this modeling approach. First, the task estimates can be sensitive to outliers in the data, particularly with small data sets. Second, some of the task variables may be redundant and highly inter-correlated, producing unstable estimates. Third, classical multiple regression methods generally will produce task estimates that are both negative and positive, but we are only interested in a non-negative solution set. To address these problems and obtain task estimates, we applied the robust Huber regression algorithm to these data. This algorithm is found in the non-linear iterative regression procedure from the SYSTAT statistical software package (SPSS Inc. 1997). This robust regression procedure minimizes the sum of median absolute deviations (MAD) for the model; a Huber weighting function is applied to reduce the emphasis of large standardized residuals (>1.7 units). This regression method will be relatively insensitive to outliers and to non-normal error structure in the data.

Another advantage of using an iterative regression is that parameter estimates can be selectively constrained to a range or fixed. To produce non-negative parameter estimates for this analysis, we set the lower bound for each task estimate to the minimum value observed in the data. Finally, in applying this model, it was observed that time data for some tasks were highly inter-correlated. Time spent in these tasks was combined into larger categories to produce stable estimates. The categories that were combined were *computer data entry or retrieval* and *office/business machine*, and *meeting*, *lunch/break*, and *other*. The task estimates produced by the regression method for these combined categories represents a weighted average of the task-specific estimates from the other estimation methods (see Appendix).

2.4.7 - Comparison of Methods

Exposure estimates determined from the different methods for recreating a subject's day were compared to the personal exposure data extracted for that subject. To estimate how far the estimates were from the actual measurements, while accounting for the observed true standard deviation of a subject's day, the following formula was used:

$$\text{deviation} = \frac{mean_{true} - mean_{estimated}}{SD_{true}} \qquad 2.11$$

This approach standardizes the estimated error for each subject's observation so that we can compare the accuracy of the task-based estimate relative to the variability within a day. The mean of these deviations for a particular estimation method provides a measure of the relative accuracy (bias) in the personal estimates; the SD of these deviations gives a measure of the precision.

2.4.8 - *Other* Task Category

Through the process of doing the robust regression modeling, we determined that it was necessary to account for time logged during the reported work shift that was not assigned to a specific job task. Exposure during these unreported intervals was assigned to *other* (task 33) by default. In most subjects this miscellaneous category accounts for a fairly small (<10%) percentage of workday time.